Solution 1: Hard Margin Classifier

(a) The function is symmetric, as we can prove in the following way:

$$k(\mathbf{x}, \tilde{\mathbf{x}}) = \mathbf{x}^T \tilde{\mathbf{x}} = \tilde{\mathbf{x}}^T \mathbf{x} = k(\tilde{\mathbf{x}}, \mathbf{x})$$
(1)

To check if the kernel gram matrix is positive definite, we will remember the definition of \mathbf{x}

$$\mathbf{x} = \left\{ \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)} \right\} \in \mathbb{R}^{p \times n} \tag{2}$$

Taking that into account, the kernel gramn matrix is defined as:

$$\mathbf{K} = \begin{pmatrix} \langle \mathbf{x}^{(1)}, \mathbf{x}^{(1)} \rangle & \langle \mathbf{x}^{(1)}, \mathbf{x}^{(2)} \rangle & \cdots & \langle \mathbf{x}^{(1)}, \mathbf{x}^{(n)} \rangle \\ \langle \mathbf{x}^{(2)}, \mathbf{x}^{(1)} \rangle & \langle \mathbf{x}^{(2)}, \mathbf{x}^{(2)} \rangle & \cdots & \langle \mathbf{x}^{(2)}, \mathbf{x}^{(n)} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \mathbf{x}^{(n)}, \mathbf{x}^{(1)} \rangle & \langle \mathbf{x}^{(n)}, \mathbf{x}^{(2)} \rangle & \cdots & \langle \mathbf{x}^{(n)}, \mathbf{x}^{(n)} \rangle \end{pmatrix}$$

$$= \left\{ \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)} \right\}^{T} \left\{ \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)} \right\}$$

$$= \mathbf{x}^{T} \mathbf{x} \in \mathbb{R}^{n \times n}$$
(3)

$$\mathbf{a}^{T}\mathbf{K}\mathbf{a} = \mathbf{a}^{T}\mathbf{x}^{T}\mathbf{x}\mathbf{a}$$

$$= (\mathbf{a}\mathbf{x})^{T}(\mathbf{a}\mathbf{x})$$

$$= \mathbf{z}^{T}\mathbf{z}$$

$$= \|\mathbf{z}\|_{2}^{2} > 0$$
(4)

We can conclude that this function is a kernel.

(b) The function is not a kernel, as we can prove that the kernel gram matrix is not positive definite. We will use $\mathbf{x}^{(1)} = \frac{\pi}{2}$ and a = 1:

$$\mathbf{K} = k(\mathbf{x}^{(1)}, \mathbf{x}^{(1)}) = \cos\left(\frac{\pi}{2} + \frac{\pi}{2}\right) = -1$$

$$\mathbf{a}^T \mathbf{K} \mathbf{a} = 1 \cdot -1 \cdot 1 = -1 < 0$$
(5)

(c) The function is not a Kernel, we can prove that the kernel gram matrix is not positive definite by using an example, let us take $\mathbf{x}^{(1)} = 1$ and $\mathbf{x}^{(2)} = 2$, and $a = (1, -1)^T$:

$$\mathbf{K} = \begin{pmatrix} max(\mathbf{x}^{(1)}, \mathbf{x}^{(1)}) & max(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}) \\ max(\mathbf{x}^{(2)}, \mathbf{x}^{(1)}) & max(\mathbf{x}^{(2)}, \mathbf{x}^{(2)}) \end{pmatrix} = \begin{pmatrix} 1 & 2 \\ 2 & 2 \end{pmatrix}$$
(6)

$$\mathbf{a}^{T}\mathbf{K}\mathbf{a} = (1, -1) \cdot \begin{pmatrix} 1 & 2 \\ 2 & 2 \end{pmatrix} \cdot (1, -1)^{T}$$
$$= (-1, 0) \cdot (1, -1)^{T}$$
$$= -1$$
 (7)

- (d) In this case, we can use properties of the kernels to prove that the function is indeed a kernel.
 - Multiplying a kernel by a non-negative scalar always results in a kernel. Accordingly, we can say that $\alpha k_1(\mathbf{x}, \tilde{\mathbf{x}})$ and $\beta k_2(\mathbf{x}, \tilde{\mathbf{x}})$ are kernels.
 - The sum of two kernels always results in a kernel. Accordingly, we can say that $\alpha k_1(\mathbf{x}, \tilde{\mathbf{x}}) + \beta k_2(\mathbf{x}, \tilde{\mathbf{x}})$ is a kernel.